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Risk and College Majors

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Risk Associated With Different College Majors

Abstract - When students choose a certain field of study in college, some opportunities are instantly forgone. Since different types of educations have varying degrees of forgone opportunities, risk is associated with educational choices. The extent to which these educational choices impose a risk on the individual is studied here. It is hypothesized that more technically oriented and job-specific type educations will have a higher risk than less restrictive liberal arts type educations. Using a large sample drawn from the National Longitudinal Survey of Labor Market Experience of Youth, this paper examines the presence and nature of risk across the different areas of study. Initial analysis reveals that compared to other areas of study, engineers and scientists have a high average income and a high variance in those incomes. Using standard linear regression analysis to control for background variables, it is found that in general, this variance is significant and positively correlated to the higher paying, more technical fields.

Introduction

There have been numerous studies to show that students in engineering, and scientifically oriented fields typically have higher average earnings than students in broader studies like the humanities and English (Altonji, 1993; Angle and Wissmann, 1981; Berger, 1988 "cohort"; Reed and Miller, 1970). The question arises as to why there is a difference. While there are probably many different factors for the wage differentials, risk must be considered one of those factors. If different risks are associated with different majors, it would certainly be feasible that wage differentials would arise.

What leads to different magnitudes of risk? Presumably the job-specific training inherent in the field of study would play a large role in determining the amount of risk. Gary Becker has touched on this issue when analyzing the returns to job specific training and general training within a firm. Becker defined general training as "being useful to many firms besides those providing it" (Becker, p.19), whereas job-specific training is only useful to one firm. This logic can be extended a step further to include types of education. Liberal arts-type educations should provide the equivalent of general training which can be applied to many different fields, while technical-type educations should be useful to only a few fields in the same manner as job-specific training. If a technically educated individual desires to try his/her hand at another field, or is forced to for the lack of job opportunity within his/her own field, it is likely that they will not be as apt as others with broader, more malleable educations. Hence they will suffer "risk" from specific training. In Becker's analysis, he finds that general training will not result in increased wages paid by the employer, but job-specific training will. This is because the general training can be utilized by other firms, while the specific training cannot With similar logic it can be hypothesized that those in technical fields should earn a higher wage on average, while those with liberal arts educations should earn less on average. Because of the limited application of technical fields, they are presumed to have more risk. The presence and magnitude of this risk is to be studied here. Does this risk really exist, and if so what fields are considered the least and most risky?

It would be of great interest to determine the relative riskiness of different majors. If there is a significant difference in risk, risk can be considered an important determinant of wages in certain fields of study. From this, students and others will be able to make more informed decisions when it comes to evaluating different career choices. If it is determined that there is no significant risk associated with higher average wages, then alternative explanations for wage differentials can be pursued.

Development of theory and related work

It has been established in the literature that investment in education will yield a higher return in terms of average earnings. This is consistent with human capital theory developed largely by Becker, which says that increasing one's ability, or human capital, increases one's productivity and thus a higher return on this capital may be demanded by the individual (Ehrenberg and Smith, p.299). In fact this has been the case in many recent studies. Joseph G. Altonji (1993) finds that wage coefficients are higher for college trained individuals and that wage coefficients for technical fields such as engineering are on average higher than non-technically oriented fields (48). Ritche and Herman (1970), Angle and Wissmann (1981), and Rumberger and Thomas (1993), all find similar results in their respective studies. Thus there is ample evidence that wage differentials do in fact exist for technical fields. Some possible reasons for these wage differentials can be understood through the theory of compensating wage differentials.

Existing theory says that a higher wage must be given to compensate an individual for some undesirable aspect of their job (Ehrenberg and Smith, chap 8). In the case presented here, the undesirable aspect is risk. A higher average wage must be given to individuals to compensate them for increased risk assumption. The nature of risk, however, implies unexpected results. Thus variance is another important factor when considering the element of risk. The issue of risk has only recently come to the surface in the studies of returns to education. In fact, Low and Ormiston (1991) did a study to account for risk and found that when risk considerations were included, the returns on a college degree can be reduced by as much as 90% (1125). Perhaps more intriguing is that they found that investment in, "general human capital, particularly education, tends to be risk increasing" (1128). This certainly is an element of the study presented here. If education is risk increasing, then higher wages should follow, and it seems they do. It should be noted that while Low and Ormiston's article certainly points out the importance of accounting for risk, it was concerned with risk associated with years of education, not with the type of education, as is being studied here.

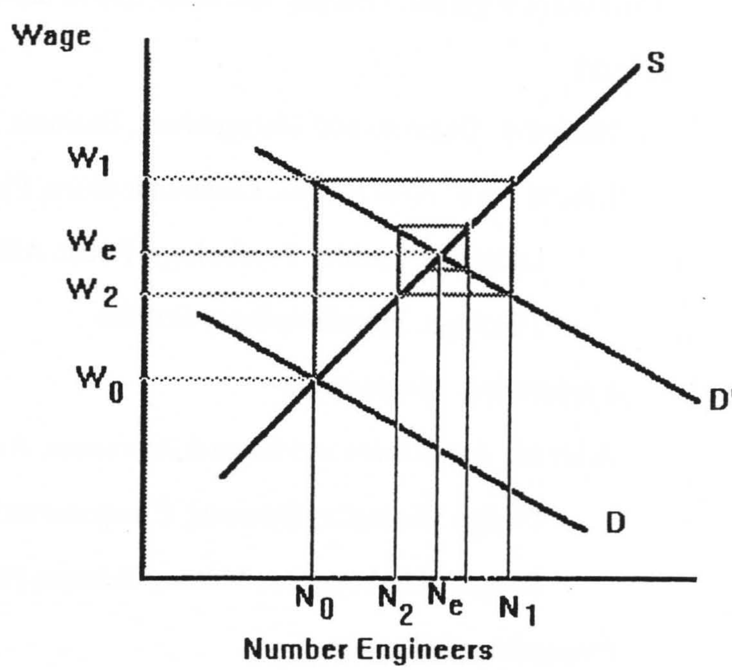
The issue of the variance in wages is still left out. Mark Berger brings this to our attention in an attempt to analyze the factors that students use when they decide upon a college major. He shows that higher expected lifetime earnings associated with different college majors will influence the number of students enrolled in that particular field. He acknowledges though, that risk aversion can affect this decision. "If as seems plausible, higher predicted streams [of earnings] tend to have larger variances and individuals are risk-averse, the omission of the variance of the predicted earnings streams from the model," will result in bias (Berger, p.427). Thus the element of risk is very important when examining educational choices and is worthy of further research.

Theory and Model

With a working foundation of why risk is important and how different aspects of it influence wages, it is possible to develop a testable hypothesis. When individuals involve themselves with higher risk, they will be compensated by a higher average return. This assumes people as a whole are risk-averse. There must be some sort of incentive for the individual to take on risk. This incentive takes the form of higher potential earnings. An analogy to investment portfolios can be drawn. Individuals may diversify their holdings and hence lower their risk. At the same time they will lower their potential return. If an individual gambles, they may earn a higher potential return, but they have an increased risk of substantial loss. It is this higher average return that provides incentive for individuals to take on risk. In the framework of the question at hand, the return on the human capital investment is the income earned from that investment. The risk is the possibility that one will not receive the expected return. If particular educations do in fact have higher risk, that risk should become apparent through a greater variance in the received wages. Thus, the risk seeker (the gambler) would pursue a high risk education, presumably a technically oriented field, in hopes of attaining the higher average earnings. The risk avoider (the diversifier) would opt for a more general education, in which the earnings, although lower, would be more predictable.

A cobweb model can be used to demonstrate one important source of risk in specialized fields. In a specialized or technically oriented field, the supply of workers cannot be adjusted rapidly. Workers must be trained and this typically requires a few years of education. In other fields, it is assumed that workers abilities are more adaptable, and thus the supply of workers is more responsive to changing demands. In the technical fields, however, the lag in the supply responsiveness can result in boom and bust cycles for wages. (see graph below) Richard Freeman shows that, "the supply of new engineering B.S. graduates depends - because of the four year training period - on salaries about four years earlier and is predetermined for each year...with supply dependent on past conditions and salaries on current conditions, the models have recursive structures that produce endogenous cyclic fluctuations" (Freeman, p.236). If there is an increased demand for, say engineers, then since the supply of engineers is fixed in the short run, the wages for engineers will increase. This will entice more people to become engineers. But the perceived wage at the time people decide to study engineering (W_1) will be above market equilibrium when the new supply of engineers hits the work force. Thus we have an oversupply of engineers. Using the same logic backwards, we end up with a shortage of engineers again when wages fall to W_2. (Ehrenberg and Smith, pp.311-313). This cycle goes on until equilibrium is reached. The result is that earnings in technically oriented fields may be unpredictable and vary more.

Cobweb Model



One important limitation of this model is that the demand curve must be flatter, or more elastic, than the supply curve. If this is not the case, wages will not converge to equilibrium, but rather diverge. It is likely, however, that the demand curve will be flatter because labor supply has typically been believed to be relatively inelastic. In any event, if this were not the case, incredible variance in earnings would be observed. Wages for engineers and the like would fluctuate violently up and down. Since the observed scenario is that wages do not, there is strong reason to believe that the demand curve is flatter than the supply curve.

It is now possible to make the hypothesis that higher risk educations should yield higher average earnings with greater variance. This follows from the idea that the increased assumption of risk must be rewarded. The nature of the risk, though, is that the return will be unpredictable. Hence the variation in earnings. Thus a finding of higher earnings and higher variation in earnings in the more technical fields is what is expected.

Development of empirical model

In order to test the hypothesis that educations with higher average earnings have higher risk associated with them, a classification of what constitutes a high risk education must be presented. Perhaps the best way to tackle this problem is simply to group similar education's together. Berger has done this in his work. He sets up five basic areas as follows:

-Business: Business and Management, Business Technology

-Liberal Arts: Area studies, Communications, Fine and Applied Arts, Foreign Language, Letters, Psychology, Public Affairs and Services, Social Sciences, Theology, Interdisciplinary Studies

-Engineering: Engineering

-Science: Agriculture and Natural Resources, Architecture and Environmental, Design, Biological Sciences, Computer and Information Sciences, Library Science, Mathematics, Military Science, Physical Sciences.

-Education: Education

This seems reasonable and usable (Berger, p.428). But now we need to rank these areas in terms of their riskiness.

Scientific fields and engineering majors can be considered high risk. These fields require a high degree of specialization and have limited applications in the work force. The fundamental argument for the riskiness of a given major is the degree of specialization associated with it. It is assumed that Engineers have the highest level of specialization, with science majors following close behind. Science majors are assumed to be less risky because they probably have slightly more options available to them. They can pursue academic type fields, research fields, or apply their expertise in the corporate world whereas an engineer is strictly limited to his/her chosen specialty in engineering. The other end of the spectrum is not as easy. The liberal arts education would, under the existing criterion be the least risky education. This follows naturally from the idea that a liberal arts education does not restrict an individual. It offers a fundamental education which can be applied to many different occupations, unlike the engineering or science fields. This is in line with existing rhetoric from the educational system. That is, liberal arts colleges or studies, through varied course work, allow individuals to be more adaptable in changing work environments. This could be interpreted as risk reducing in the present context.

Classifying the education and business groups according to risk, however, is less straight forward. It simply is a matter of educated guessing as to which fields are more restrictive than others. It should be kept in mind, however, that this methodology is somewhat arbitrary and highly intuitive in nature and there certainly is an opportunity here for developing a better criterion. The assumption that a business graduate is less restricted than an education graduate is given in light of the fact that there are more areas in the work force under which a business major can be utilized. Thus it is presumed that business majors have a wider range of employment opportunities than an education major.

Table 1: Rankings of Risk

Rank	Area of Study
1 (The most risky)	Engineering
2	Science
3	Education
4	Business
5 (The least risky)	Liberal Arts

For this reason education is viewed as a relatively riskier education than business. A summary of the hypothesized rankings of earnings and variance by area of study is presented in Table 1.

The Empirical Model and Results

With the classification and riskiness of majors defined, it is now possible to present methods for testing the hypothesis. The National Longitudinal Survey of Labor Market Experience of Youth (NLSY) is used to extract data about individuals. The NLSY is a survey beginning in 1979 of youth aged 14 to 22. The data consisted of a cross-sectional sample of individuals who had received a bachelor's degree or higher by 1988. The earnings of these individuals during the years of 1987 to 1990 were used in the analysis.

The theories of human capital and compensating wage differentials along with the cobweb model suggest the following research hypothesis:

> **There should be a direct relationship between the "risk" of an area of study and the average earnings in that area. Specifically, we expect areas of study to follow the rankings presented in Table 1 in terms of both average earnings and risk as measured by variance in earnings.**

This dictates that we need to study the variance and average earnings in the different respective areas of study. The variance will give us some measure of risk and our hypothesis says that this should be greater with higher average earnings. The variance should be influenced individually by human capital and compensating wage differential considerations, and over time through cobweb effects. To begin, a surface analysis was done that looked at average earnings and variance of the different educational fields without regard to any background variables.

The data on earnings was gathered in an unusual way. Earnings, consisting of all monetary compensation for work in the time period, was gathered for each individual over the four year period of 1987, 1988, 1989, and 1990. For each year, the earnings were considered as an individual case. This gave us four observations for each individual, which in effect, quadrupled the sample size. This creates a "pool" of engineers, scientists, etc., for which earnings can be measured in each specific year. This method allowed us to better get at the notion of variance. Since risk is associated with variation in earnings, average earnings over four years could not be used because it would average out the variance associated with time!

A total, or the lifetime earnings, can't be used because it too, might average out variance if income is low in one year and high in another. Thus to get a measure of the true variation in earnings, the yearly earnings must be considered on an individual basis. The data for the four years of earnings are then pooled together and adjusted for inflation using the consumer price index from the U.S. Bureau of Labor Statistics. The figures are expressed in 1982-1984 dollars. These initial results are presented in Table 2.

Table 2 shows that the risk effect appears to be present, since the areas with the high average earnings also have the highest variation in earnings. This provides direct support for the research hypothesis. It is seen that Engineers have average earnings of $10,000 greater than liberal arts majors, but they also have twice as much variation in those earnings. For example, the standard deviation of engineer's earnings is approximately $30,000, which is more than twice the standard deviation of liberal arts

Table 2: Means and Standard Deviations by Area of study*

Major	Mean income	Standard deviation	Number of cases
Engineering	30,056	32,232	308
Science	20,043	27,108	952
Education	15,587	10,331	517
Business	23,042	21,164	1114
Liberal arts	17,755	13,175	1218
Law	40,722	64,965	67

*** all means and standard deviations are significantly different at the alpha = 0.01 level except law and engineering, in which the difference in means is significant at the 0.1 level.**

majors. There are, however, some departures from the theory. In terms of average earnings, the business majors are higher than expected and the education majors are lower than expected, In terms of variance, only the education majors depart from predictions. The results for the area of law have been included, but since a law degree is an advanced degree, it is left out of this analysis. This is done because it would not be proper to compare the earnings of those with advanced degrees to those with just a bachelors degree. Nevertheless, it is still consistent with the research hypothesis. The specialized field of law has high average earnings and high variance in earnings.

Although the descriptive statistics shown in Table 2 support the research hypothesis, a more complete analysis would control for influences on variation in earnings that can not be attributed to the field of study. These influences can be due largely to differences in backgrounds, which may give individuals different levels of human capital. Different levels of human capital can create variation in earnings that is not due necessarily to the field of study. Other factors like work experience carry similar arguments. For these reasons, the variation due to forces outside of the area of study are controlled for using regression equations.

Table 3 presents the different variables used in the regression equations and gives a description of the background variables. The background variables of minority status, gender, AFQT score, age, and mother's education are included because of the influence they may have on wages. Minority status and gender have typically been sources of income inequality due to discrimination, job status, and other influences. For these reasons it is expected that these qualities would negatively affect earnings. The AFQT score, mother's education, and age are all related to the idea of human capital. The AFQT score is argued to be a proxy of ability, which would increase the human capital, and hence earnings of the individual. In the same regard, it is thought that human capital is also acquired through the family. Hence the amount of education of the mother should also positively affect the human capital of the individual. Finally, as one grows older, he/she acquires more skills which should again, increase earnings.

Table 3: Definitions

Variable	Definition	Mean
LA	Respondent was a liberal arts major (1 = liberal arts major; 0 = non-liberal arts major)	0.26
BUS	Respondent was a business major (1 = business major; 0 = non-business major)	0.23
EDUC	Respondent was an education major (1 = education major; 0 = non-education major)	0.11
SCI	Respondent was a science major (1 = science major; 0 = non-science major)	0.20
ENG	Respondent was an engineering major (1 = engineering major; 0 = non-engineering major)	0.06
LAW	Respondent has a law degree (1 = obtained law degree; 0 = no law degree)	0.02
NEC	Respondent was not elsewhere classifiable - the major is unknown (1= major is unknown; 0 = major is classifiable)	0.12
RISK	The standard error in regression equations predicting income for different majors. (the variance in earnings)	18891
AFQT	Respondent's score on the Armed Forces Qualifying Test	74.57
AGE	Age of respondent	17.65
MOTHEDC	Years of education of the respondents mother	13.17
FEMALE	Respondent was female (1 = female; 0 = male)	0.51
ADVDGR	Respondent obtained an advanced degree (1 = obtained advance degree; 0 = no advanced degree)	0.13
AVGHRS	Average hours worked per year pre-1988	1182
MINORITY	Respondent was a black or Hispanic minority (1 = black or Hispanic minority; 0 = not a minority)	0.09

The human capital idea is very important to control for, as it is believed this is a primary determinant of earnings. Thus, variables to account for work experience and advanced degrees were included. These are both human capital increasing variables, so they should positively influence earnings.

A regression equation to take into consideration these background variables was executed. It is a standard OLS linear regression.[1]

$$[INCOME] = a_0 + a_1[BUS] + a_2[ENG] + a_3[EDUC] + a_4[SCI] +$$
$$a_5[LAW] + a_5[NEC] + a_7[MINORITY] + a_8[AFQT] + a_9[FEMALE] +$$
$$a_{10}[AGE] + a_{11}[MOTHEDC] + a_{12}[ADVDGR] + a_{13}[AVGHRS]. \qquad (1).$$

This regression incorporates the use of dummy variables. The variables for educational major, minority status, gender, and advanced degrees are all dummies. They take a value of one only if the criteria is met. The liberal arts major was left out as the omitted group. This provides a reference for which to compare the coefficients of the other educational fields. Since liberal arts is hypothesized to be the least risky, all the coefficients for educational field should be positive and significant.

The results of this initial regression provide a ranking of average earnings and generally supports the research hypothesis that high earnings are directly related to higher risk as measured by variation in earnings. The results are displayed in Table 4 as model 1. It is observed that the relative position of the educational fields has remained about the same, as in Table 2. Engineers earn the most, with the highest positive coefficient. The coefficient shows that, ceteris paribus, they earn $11212 more than liberal arts majors, on average. The engineers are followed by science majors, which have moved up to be more in line with theory, followed by business majors, followed by liberal arts majors (the omitted group), and lastly education majors. The coefficients for all of the majors are significant at least the .016 level, except it should be noted that the education major coefficient is only significant at the .15 level. Nonetheless, the coefficient to EDUC remains deviant from the theory. This regression, however, does not provide a measure of risk for individual areas of study.

In order to construct a more satisfactory measure of risk in earnings for each area of study, regression equations for each major were executed. These regressions selected upon a specific educational field, and included the same control variables as equation 1. The standard error of these equations is used as an estimate of the variation in earnings

Table 4: Regression Results (Standard errors in parenthesis)

Variable	Model 1	Model 2
ENG	11,212***	
	(1,912)	
SCI	3,910**	
	(1,268)	
BUS	2,960*	
	(1,222)	
EDUC	-2,215	
	(1,519)	
LAW	22,468***	
	(3.533)	
NEC	-386	
	(1,587)	
RISK		0.328***
		(0.041)
AVGHRS	7.73***	8.22***
	(1.10)	(1.09)
ADVDGR	8,169***	8,559***
	(1,332)	(1285)
FEMALE	-6,992***	-7,521***
	(887)	(871)
AFQT	45.5*	55.7*
	(24.7)	(24.1)
AGE	282	192
	(294)	(292)
MINORITY	296	1,090
	(1576)	(1,568)
MOTHEDC	34	67
	(180)	(179)
CONSTANT	5,310	1,352
	(5,397)	(5,371)
Adjusted R-square	0.114	0.109
N	2852	2852

*** significant a the 0.001 level
** significant at the 0.01 level
* significant at the 0.1 level

that couldn't be explained by different background variables. This is the proxy for risk.. The results of these regressions are presented in Table 5.

Table 5: Independent regression results (Standard errors in parenthesis)

Variable	Engineers	Science	Business	Liberal arts	Education	Law
FEMALE	-9,867 (8,854)	-3,268 (2,757)	-8,668*** (1,093)	-5,321*** (977)	-3,846** (1,328)	-5,931 (24,053)
ADVDGR	-4,213 (10,414)	20,798*** (3,768)	8,597*** (1,734)	1,704 (1,467)	2,126 (1,544)	N/A
AVGHRS	15.29* (7.75)	9.47* (3.81)	9.97*** (1.40)	8.43*** (1.20)	4.84** (1.63)	-248** (72)
AGE	1,510 (2,032)	1,537* (889)	-444 (391)	-861** (322)	-699* (422)	58,975*** (14,702)
MINORITY	-4,821 (9,865)	-5,108 (6,901)	-1,961 (1,911)	2,928 (1,892)	3,917 (2,376)	-75,967 (52,461)
AFQT	-81.6 (249.0)	-108.1 (99.3)	50.3 (34.3)	91.0*** (25.6)	35.4 (37.4)	3933.7* (1761.4)
MOTHEDC	-1,577 (1,458)	-432 (582)	185 (211)	154 (199)	-268 (301)	-14,480* (7,210)
CONSTANT	18,425 (44,137)	-612 (16,388)	17,196* (7,144)	20,025*** (5,870)	27,891*** (7,233)	976,900*** (244,315)
Adjusted R-square	0.045	0.073	0.214	0.135	0.037	0.248
N	185	573	667	744	330	49
Standard Error (Risk)	38,583	31,387	13,871	12,765	10,122	63,443

*** significant at the 0.001 level
** significant at the 0.01 level
* significant at the 0.1 level

The individual regressions show some interesting results. It is not in the scope of this project to analyze the reasons behind the differences in the regression equations, but it is interesting to notice that the significance of different background variables differ between majors. For example, gender has a very significant effect on earnings for every major except engineering, science, and law. The standard errors of these regression is the primary focus of this project.

Table 5 demonstrates that the standard errors, or riskiness of the different majors aligns in exactly the same order as the rank of average earnings. The standard errors of the individual regression equations are presented in the last row of Table 5. The engineers have the highest standard error in their earnings, and the education majors the lowest. This lends strong support to the hypothesis. The fields of study with the most technical training, and the highest average earnings, have the highest variance in their earnings.

As a final, ultimate test of the hypothesis, a regression using the standard error in earnings for each major as a proxy for risk was developed. The regression was as follows:

$$[INCOME] = a_0 + a_1[RISK] + a_2[MINORITY] + a_3[AGE] + a_4[FEMALE] + a_5[ADVDGR] + a_6[MOTHEDC] + a_7[AFQT] + a_8[AVGHRS]. \qquad (2).$$

The values for the regression coefficients are shown in Table 3 as model 2. The variable [RISK] is the standard error associated with the different majors. (see Table 5) The coefficient for this variable is both positive and highly significant. This means that risk does matter, and it positively influences wages. The coefficient for the risk variable is conceptually abstract to analyze. It shows that for every $1 increase in the standard error of earnings, there is a $0.32 increase in earnings. The important finding is that it is both positive and significant. This result is consistent with the research hypothesis that higher average earnings have higher variances in earnings.

The fact that the education majors lie at the bottom, both in terms of earnings and variance is the only inconsistent result. It was believed that they would be in the middle. An education major would be riskier than liberal arts and business, but not as risky as engineering or science. It must be the case that something else is influencing the income and variance of education majors downward. It is possible that the educational field is limited in its ability to reward risk with higher earnings because of budgetary constraints, often typical of government institutions. Additionally, general acceptance of uniform teachers salaries and tenure contracts could be contributing to the low variance in income. Another possibility is that the educational field is more immune to the business cycle as school enrollments, populations, etc. are unaffected by the business cycle. This creates more stability and hence less risk. The fact that education majors have the lowest earnings tends to be in agreement with other studies that find technical fields and business majors to have high incomes and liberal arts educations and education majors to have low incomes (Angle and Wissmann, 1981; Berger, 1988; Rumberger, 1993).

In a brief analysis of the background variables, some interesting results can be seen from Table 4. Of the inherent background variables, only gender and ability are significant. They both agree with the predicted value of their signs. Gender appears to be of great importance. The coefficient for gender is larger than any other background variable and is highly significant. This result is of particular importance in analysis of this type of research. It is commonly believed that gender is important because males tend to dominate technically oriented fields. It would be thought that after controlling for gender, the effect on income of a technical major will diminish because of the large male constituency. Indeed, this seems to be the case. By including gender into the regression equation, the gap between engineers and other fields decreased.

The background variables of minority status, mother's education, and age are all insignificant. (see Table 4) It is interesting to see though, that some of these variables become significant in the individual regressions. (see Table 5) It is also interesting to see in Table 4, that while insignificant, the minority variable carries a positive coefficient. It is surprising at first, but is consistent with the idea that for college educated individuals, there is a premium on minorities for recruitment reasons. The control variables of advanced degree and average hours worked behaved as predicted. They were highly significant and positive. The advance degree increases human capital, as does work experience, which in turn raises earnings.

Limitations of the empirical model and ideas for future research

There are some very important limitations of this project. First, inevitable difficulties arise when trying to look at the riskiness of different majors. It is assumed, quite reasonably, that part of the risk in a certain field is that you may not be able to find a job, or find very little. But there is also voluntary withdrawal from the work place. It is very difficult, if not impossible to distinguish between those that are willingly removed from the work force and those that are not. This is a problem that has plagued economists for years. The consequence of this is that some of those people who were voluntarily out of the work force may have been included in the data, skewing the variance and hence risk associated with different majors. It also is possible that some individuals attend school with no intention of utilizing the degree they received. It is doubtful, however, that these individuals would choose a highly demanding course of study such as engineering or science, only to abandon their educations. Therefore a bias may exist if those people who choose not to work, or are not committed to their major, are concentrated in one area of study.

Second, the existing data have some shortcomings. The NLSY is limited with respect to income measurements. Since the survey is recent and most of the interviewees have only been in the work force for a few years, data on life time earnings is not available, and it was only possible to gather income for a four year period. This time constraint creates distortions because some occupations may have steeper age-earnings profiles. That is, some fields may reward work experience more than others. If technical fields have higher earnings earlier in the life-cycle than other fields, the earnings for the technical fields may be skewed upwards. Of course, just the opposite may be true, which would skew earnings downward. Ideally, earnings fluctuations could be analyzed for a life-cycle. This would reveal the entire risk associated with different majors.

This time constraint is further restrictive because it does not fully capture the effect of job choice on earnings. This could underrepresent the true variance in earnings for different fields. For example, If somebody tried to switch fields of expertise, they would likely be hurt in proportion to the limiting nature of their education. An individual that has a very limiting education, would likely suffer greater earnings losses than a person with a broader education, if they tried to enter a new field. It would not be expected that these switches in employment necessarily occur soon after entering the work force. Indeed, in Rumberger's study, he found that graduates who did not find employment within their fields of expertise had lower relative earnings (9). If this kind of effect is not captured due to the time constraint, it could skew the variance in earnings for a high risk education to be less than reality.

Third, the relative growth of each labor market may be an important variable. Freemen notes, that with the cobweb model of technical fields, "expansion [of employment opportunities] provides an important buffer to short-run cycles" (Freemen, p.237). Thus if the employment opportunities for engineers, or any field for that matter, were expanding exceptionally during 1987 to 1990, they may have provided a misleading gauge of risk because of the offsetting effect they have upon a risky field. The effects of these different fluctuations in labor markets could also be solved through life-cycle analysis. If one field grows faster than another field for an entire life-time, then it can't be considered risky if it will always provide employment, even if it is extremely technical. But if the field was only experiencing a temporary change, the effects on lifetime earnings would be minimal and total variation could be measured. Future research should incorporate a longer time period to assure against such biases.

Finally, it is important to realize that a growing trend in labor markets is to provide payment for services through employee benefits. If some particular fields utilize this form of payment more than another, as might be the case with the educational field, it may bias the average earnings of those particular fields downwards because only monetary compensation was considered in this study.

Implications and Conclusions

The results are generally consistent with the research hypothesis that more specialized fields of study have higher average earnings as well as higher variations in those earnings. Education majors, however, do not seem to fit the hypothesis. The implication of this is that individuals who pursue an education major may not be compensated for the risk they are taking. The data would suggest that earning differentials are significantly affected by gender and any reduction in this difference must seek to understand why this is. A major implication of the results is that there is a relationship between higher incomes and higher variance, which supports the theory that earnings differentials compensate for differences in earnings-risk. It is also apparent that this conclusion is robust in the sense that both descriptive results (Table 2) and regression results were the same. Engineer and science majors consistently have higher average earnings and high variance, while liberal arts majors have lower average earnings and lower variation.

The implications on students are obvious. Students should be adequately informed of the risk associated with the advertised higher earnings of some majors, and vice versa. With this type of information, students and others may realize the old economic axiom, there is no such thing as a free lunch.

Footnotes

[1]It was debated whether to use a logarithmic equation which would look at the natural log of the income as opposed to just the "straight" data. The logarithmic equation is an off-shoot of work by Jacob Mincer and is often referred to as a Mincer-type equation. It has been found that, "a logarithmic transformation of the dependent variable is both theoretically and statistically desirable." (Angle and Wissmann, p.25) This is based on the premise that the income of individuals follows a logarithmic profile over time. In our study, however, we will run into trouble using this type of equation. Since it will become necessary to run regression equations for each educational field (to get a measure of variance) the logarithmic conversion will not be satisfactory. It can be mathematically shown that the transformation can change the averages and standard deviations of the data. Normally, this would not be a problem but since we need to compare the regressions, this kind of transformation is unacceptable. It creates the possibility that the relative rankings for each area of study, which is critical to the hypothesis, may be jumbled by the transformation. Furthermore, since the earnings data only covers a period of four years, it is unlikely that the logarithmic profile is observable. Indeed, the regression was run again including $[AGE]^2$ and $[AVGHRS]^2$ to see if the logarithmic effect was observable. Neither variable was significant.

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